A Review on *H-M*ining-(High Utility Item sets of Mining)

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Abstract
High utility pattern mining is a rising information science task, which comprises of finding patterns having a high significance in databases. The utility of a pattern can be estimated regarding different target criteria's, for example, its benefit, recurrence, and weight. Among the different sorts of high utility patterns that can be found in databases, high utility itemsets are the most considered. A high utility itemset is a lot of qualities that shows up in a database and has a high significance to the client, as estimated by an utility capacity. High utility itemset mining sums up the issue of successive itemset mining by thinking about thing amounts and loads. A well known use of high utility itemset mining is to find all arrangements of things bought together by clients that return a high benefit. This paper gives a prologue to high utility itemsets mining, audits the best in class calculations

Keywords: high-utility itemset mining, frequent pattern mining, itemsets, pattern mining.

1 Introduction

The objective of data mining is to concentrate patterns or train models from databases to comprehend the past or foresee what's to come. Different kinds of data mining algorithms have been proposed to investigate data [1, 38]. A few algorithms produce models that work as secret elements. For instance, a few sorts of neural networks are intended to perform forecasts all around precisely however can't be effectively deciphered by people. To extricate learning from data that can be comprehended by people, pattern mining algorithms are structured [27, 28]. The objective is to find patterns in data that are intriguing, helpful, as well as sudden. A bit of leeway of pattern mining more than a few other data mining methodologies is that finding patterns is a sort of solo learning as it doesn't require marked data. Patterns can be legitimately extricated from crude data, and after that be utilized to get data and bolster basic leadership. Pattern mining algorithms have been intended to separate different kinds of patterns, each giving diverse data to the client, and for extricating patterns from various sorts of data. Prevalent kinds of patterns are sequential patterns [27], itemsets [28], bunches, patterns, anomalies, and graph structures [38].

Research on pattern mining algorithms has begun during the 1990s with algorithms to find successive patterns in databases [2]. The primary calculation for continuous pattern mining is Apriori [3]. It is intended to find visit itemsets in client exchange databases. An exchange database is a lot of records (transactions) demonstrating the things acquired by clients at various occasions. A successive itemset is a gathering of qualities (things) that is every now and again acquired by clients (shows up in numerous transactions) of an exchange database. For instance, a successive itemset in a database might be that numerous clients purchase the thing noodles with the thing zesty sauce. Such patterns are effectively reasonable by people and can be utilized to help basic leadership. For example, the pattern {noodles, fiery sauce} can be utilized to take advertising choices, for example, co-advancing noodles with zesty sauce. The disclosure of successive itemsets is a well-examined data mining task, and has applications in various areas. It very well may be seen as the general undertaking of dissecting a database to discover co-happening esteems (things) in a lot of database records (transactions) [10, 16, 20, 37, 61].

To address this constraint of successive itemset mining, a rising examination zone is the disclosure of high utility patterns in databases [31, 52, 56, 58, 59 and 62]. The objective of utility mining is to find patterns that have a high utility (a high significance to the client), where the utility of a pattern is communicated as far as an utility capacity. A utility capacity can be characterized as far as criteria, for example, the benefit produced by the clearance of a thing or the time spent on site pages. Different sorts of high utility patterns have been examined. This section overviews explore on the most mainstream type, which is high utility itemsets [83]. Mining high utility itemsets can be viewed as a speculation of the issue of successive itemset mining where the information is an exchange database where everything has a weight speaking to its significance, and where things can have non paired amounts in transactions. This general issue plan permits demonstrating different errands, for example, finding all itemsets (sets of things) that return a high benefit in an exchange database, discovering sets of site pages where clients invest a lot of energy, or discovering every single successive pattern as in customary regular pattern mining. High utility itemset mining is a functioning examination region. This section gives a complete overview of the field.

2 Problem Definitions

This segment presents the issue of high utility itemset mining [31, 52, 56, 58, 59]. And afterward clarifies how it is summed up. Key Algorithms of high utility itemset mining are introduced.

2.1 High Utility Itemset Mining.

The issue of continuous itemset mining comprises of removing patterns from an exchange database.

The issue of continuous itemset mining has been read for over two decades. Various algorithms have been proposed to find incessant patterns proficiently, including Apriori [2], FP-Growth [39], Eclat [41], LCM [51] and H-Mine [52]. Albeit visit itemset mining has numerous applications, a solid presumption of regular itemset mining is that continuous patterns are helpful or intriguing to the client, which isn't in every case genuine. To address this significant impediment of conventional regular pattern mining, it has been summed up as high utility itemset mining, where things are commented on with numerical qualities and patterns are chosen dependent on a client characterized utility capacity.

2.2 High Utility Itemset Mining

The assignment of high utility itemset mining [31, 52, 56, 58, 59] comprises of finding patterns in a summed up kind of exchange database called quantitative exchange database, where extra data is given, that is the amounts of things in transactions, and loads showing the overall significance of everything to the client.

2.2.1 High-Utility Itemsets Mining algorithms

These algorithms find patterns having a high utility (significance) in various types of data.

a) Algorithms for mining high utility itemsets in a transaction database having profit information

i. The **EFIM** algorithm

Acquainted a few new thoughts with all the more proficiently find high-utility itemsets EFIM depends on two new upper-limits named reexamined sub-tree utility and nearby utility to all the more adequately prune the pursuit space. It additionally presents a novel cluster based utility checking method named Fast Utility Counting to compute these upper-limits in direct reality. Besides, to diminish the expense of database examines, EFIM proposes proficient database projection and exchange blending methods named High-utility Database Projection (HDP) and High-utility Transaction Merging (HTM), likewise performed in straight time.

ii. The **FHM** algorithm

A tale procedure dependent on the investigation of thing co-occurrences to lessen the quantity of join tasks The FHM (Fast High-Utility Miner) diminishes the quantity of join tasks by up to 95 % and is up to multiple times quicker than the best in class calculation HUI-Miner.

iii. The **HUI-Miner** algorithm

HUI- HUI-Miner utilizes a novel structure, called utility-list, to store both the utility data about an itemsets and the heuristic data for pruning the inquiry space of HUI-Miner. By maintaining a strategic distance from the costly generation and utility computation of various up-and-comer itemsets, HUI-Miner can proficiently mine high utility itemsets from the utility records constructed from a mined database.

iv. The **UFH** algorithm

HUI-Miner utilizes a novel structure, called utility-list, to store both the utility data about an itemsets and the heuristic data for pruning the inquiry space of HUI-Miner. By maintaining a strategic distance from the costly generation and utility computation of various up-and-comer itemsets, HUI-Miner can proficiently mine high utility itemsets from the utility records constructed from a mined database.

v. The **IHUP** algorithm

Incremental and interactive data mining give the capacity to utilize past data structures and mining brings about request to decrease superfluous estimations when a database is refreshed, or when the base threshold is changed. The three novel tree structures to proficiently perform incremental and interactive HUP mining, the primary tree structure, Incremental HUP Lexicographic Tree (IHUPL-Tree), is organized according to a thing's lexicographic request. It can catch the incremental data with no rebuilding task. The second tree structure is the IHUP Transaction Frequency Tree (IHUPTF-Tree), which acquires a compact size by organizing items according to their transaction frequency (descending order). To diminish the mining time, the third tree, IHUP-Transaction-Weighted Utilization Tree (IHUPTWU-Tree) is planned dependent on the TWU estimation of items in descending order.

The following algorithms also used for discovering patterns having a high utility (importance) in different kinds of data.

vi).The Two-Phase algorithm vii).The UP-Growth algorithm viii).The UP-Hist algorithm
ix).The d2HUP algorithm x).The HUP-Miner algorithm xi).The mHUIMiner algorithm
xii).The HMiner algorithm xiii).The ULB-Miner algorithm xiv).The UP-Growth+ algorithm

b) Algorithm for efficiently mining high-utility itemsets with length constraints in a transaction database

- The FHM+ Algorithm

FHM+ for mining HUIs, while considering length constraints. To discover HUIs efficiently with length constraints, FHM+ introduces the concept of Length UpperBound Reduction (LUR), and two novel upper-bounds on the utility of itemsets.

c) Algorithm for mining correlated high-utility itemsets in a transaction database

- The FCHM_bond algorithm and The FCHM_allconfidence algorithm, to use the bond measure

FCHM (Fast Correlated high-utility itemset Miner), to efficiently discover correlated high-utility itemsets using the bond measure, FCHM is up to two orders of magnitude faster than FHM, and can discover more than five orders of magnitude less patterns by only mining correlated HUIs.

d) Algorithm for mining high-utility itemsets in a transaction database containing negative unit profit values

- The FHN Algorithm (Fast High-utility Miner)

Discovers HUIs without generating candidates and introduces several strategies to handle items with negative unit profits efficiently. Experimental results with six real-life datasets shows that FHN is up to 500 times faster and can use up to 250 times less memory than the state-of-the-art algorithm HUINIV-Mine

- The HUINIV-Mine Algorithm

HUINIV (High Utility Itemsets with Negative Item Values)-Mine, for efficiently and effectively mining high utility itemsets from large databases with consideration of negative item values

e) Algorithm for mining on-shelf high-utility itemsets in a transaction database containing information about time periods of items

- The FOSHU Algorithm

Incremental and interactive data mining give the capacity to utilize past data structures and mining brings about request to decrease superfluous estimations when a database is refreshed, or when the base threshold is changed. The three novel tree structures to proficiently perform incremental and interactive HUP mining, the primary tree structure, Incremental HUP Lexicographic Tree (IHUPL-Tree), is organized according to a thing's lexicographic request. It can catch the incremental data with no rebuilding task. The second tree structure is the IHUP Transaction Frequency Tree (IHUPTF-Tree), which acquires a compact size by organizing items according to their transaction frequency (descending order). To diminish the mining time, the third tree, IHUP-Transaction-Weighted Utilization Tree (IHUPTWU-Tree) is planned dependent on the TWU estimation of items in descending order.

The Algorithms listed bellow, classified according to type of search on database, techniques used and etc., with name and small description, which are very useful in HUIs.

f) Algorithm for mining frequent high-utility itemsets in a transaction database

1.The TS-HOUN Algorithm 2.The FHMFreq Algorithm, a variation of the FHM Algorithm

g) Algorithm for incremental high-utility itemset mining in a transaction database

1.The EIHI Algorithm 2.The HUI-LIST-INS Algorithm

h) Algorithm for mining concise representations of high-utility itemsets in a transaction database

1.The HUG-Miner Algorithm for mining high-utility generators 2.The GHUI-Miner Algorithm for mining generators of high-utility itemsets 3.The MinFHM Algorithm for mining minimal high-utility itemsets 4.The EFIM-Closed Algorithm for mining closed high-utility itemsets 5.The CHUI-Miner Algorithm for mining closed high-utility itemsets 6.The CHUD Algorithm for mining closed high-utility itemsets 7.The CHUI-Miner(Max) Algorithm for mining maximal high utility itemsets 8.Algorithm for mining the skyline high-utility itemsets in a transaction database 9.The SkyMine Algorithm

i) Algorithm for mining the top-k high-utility itemsets in a transaction database

1.The TKU Algorithm, obtained from UP-Miner under GPL license 2.The TKO-Basic Algorithm

j) Algorithms for mining the top-k high utility itemsets from a data stream with a window

The FHMDS and FHMDS-Naive Algorithms

k) Algorithm for mining frequent skyline utility patterns in a transaction database

The SFUPMinerUemax Algorithms

l) Algorithm for mining quantitative high utility itemsets in a transaction database:

The VHUQI Algorithm

m) Algorithm for mining high-utility sequential rules in a sequence database

The HUSRM Algorithm

n) Algorithm for mining high-utility sequential patterns in a sequence database

The USPAN Algorithm

o) Algorithm for mining high-utility probability sequential patterns in a sequence database

1.The PHUSPM Algorithm 2. The UHUSPM Algorithm

p) Algorithm for mining high-utility itemsets in a transaction database using evolutionary Algorithms
1.The HUIM-GA Algorithm 2.The HUIM-BPSO Algorithm 3.The HUIM-GA-tree Algorithm 4.The HUIM-BPSO-tree Algorithm 5.The HUIF-PSO Algorithm 6.The HUIF-GA Algorithm 7.The HUIF-BA Algorithm

q) Algorithm for mining high average-utility itemsets in a transaction database
1.The HAUI-Miner Algorithm for mining high average-utility itemsets 2.The EHAUPM Algorithm for mining high average-utility itemsets 3.The HAUI-MMAU Algorithm for mining high average-utility itemsets with multiple thresholds 4.The MEMU Algorithm for mining high average-utility itemsets with multiple thresholds

r) Algorithms for mining high utility episodes in a sequence of complex events (a transaction database)
1.The TUP Algorithm for mining frequent periodic patterns in a sequence of transactions (a transaction database)
2.The UP-SPAN Algorithm for mining periodic high-utility patterns (periodic patterns that yield a high profit) in a sequence of transactions (a transaction database) containing utility information

s) Algorithms for mining periodic high-utility patterns (periodic patterns that yield a high profit) in a sequence of transactions (a transaction database) containing utility information
The PHM Algorithm

t) Algorithms for discovering irregular high utility itemsets (non periodic patterns) in a transaction database with utility information
The PHM_irregular Algorithm, which is a simple variation of the PHM Algorithm

u) Algorithm for discovering local high utility itemsets in a database with utility information and timestamps
The LHUI-Miner Algorithm

v) Algorithm for discovering peak high utility itemsets in a database with utility information and timestamps
The PHUI-Miner Algorithm

2.3 A Comparison of High Utility Itemset Mining Algorithms

This segment has given an outline of some well known high utility itemset mining algorithms. The Table no 1 gives a comparison of their attributes regarding sort of inquiry (breadth-first hunt or depth-first pursuit), the quantity of phases (one or two), database portrayal (horizontal or vertical), and the most comparative frequent itemset mining algorithm.

Table no 1: Algorithms for high utility itemset mining

Algorithm	Search type	No of phases	DB representation	Extends
Two-Phase	breadth-first	Two	Horizontal	Apriori
PB	breadth-first	Two	Horizontal	Apriori
IHUP	depth-first	Two	Horizontal(prefix tree)	FP-Growth
UPGrowth(+)	depth-first	Two	Horizontal (prefix-tree)	FP-Growth
HUP-Growth	depth-first	Two	Horizontal (prefix-tree)	FP-Growth
MU-Growth	depth-first	Two	Horizontal (prefix-tree)	FP-Growth
D2HUP	depth-first	One	Vertical (hyper structure)	H-Mine
HUI-Miner	depth-first	One	Vertical (utility-lists)	Eclat
FHM	depth-first	One	Vertical (utility-lists)	Eclat
mHUIMiner	depth-first	One	Vertical (utility-lists)	Eclat
HUI-Miner*	depth-first	One	Vertical (utility-lists*)	Eclat
ULB-Miner	depth-first	One	Vertical (buffered utility-lists)	Eclat
EFIM	depth-first	One	Horizontal (with merging)	LCM

3. Research Opportunities

Despite the fact that the issue of high utility itemset mining has been read for more than 10 years, and various papers have been distributed on this subject, there are various research opportunities. We have distinguished four kinds of opportunities:

Novel applications: The first research opportunities are to apply existing pattern mining algorithms in new courses as far as application spaces. Since pattern mining algorithms are very broad, they can be connected in a huge number of spaces. Specifically, the utilization of pattern mining strategies in developing examination territories, for example, informal community investigation, the Internet of Things, sensor networks gives a few novel conceivable outcomes regarding applications.

Enhancing the performance of pattern mining algorithms: Since pattern mining can be very tedious, particularly on thick databases, huge databases, or databases containing many long transactions, much research is continued growing more

effective algorithms This is an important issue particularly for new augmentations of the high utility itemset mining issue, for example, on-rack high utility itemset mining or occasional high-utility itemset mining, which have been less explored. Numerous opportunities additionally lies in conveyed, GPU, multi-core or parallel algorithm advancement to build speed and versatility of the algorithms.

Extending pattern mining to consider more complex data: Another exploration opportunity is to grow high utility pattern mining algorithms that can be connected on complex kinds of data.

Extending pattern mining to discover more complex and meaningful types of patterns: Identified with the above opportunity, another important issue to discover more complex sorts of patterns. Additionally, another exploration opportunity is to work on the assessment of patterns utilizing for instance novel measures, since it is likewise key to guarantee that the most fascinating or helpful patterns are found.

4. Open-Source Implementations

Usage of high utility pattern mining algorithms are offered in the SPMF data mining library (http://www.philippe-fournier-viger. com/spmf/) [21, 25]. It offers more than 180 algorithms for mining patterns, for example, high utility patterns, itemsets, sequential patterns, sequential principles, occasional patterns, and affiliation rules. It is a multi-platform library created in Java and discharged under the GPL3 permit. It is intended to be effectively incorporated in other Java software programs, and can be kept running as standalone software utilizing its command-line or graphical UI. Standard datasets for seat stamping high utility itemset and pattern mining algorithms can be found on the SPMF site at http://www.philippe-fournier-viger.com/spmf/index.php?link=datasets.php.

5. Conclusion

High-utility itemset mining is a functioning field of research having various applications. This paper has displayed the issue of high-utility itemset mining, examined the principle strategies for exploring the inquiry space of itemsets, utilized by high-utility itemset mining algorithms. At that point, the paper has talked about research opportunities and open-source software.

6.References

[1]. Aggarwal,R, C.C.: Springer, Heidelberg (2015) Data mining: the textbook.

[2]. Srikant, R Agrawal, R., pp. 487–499. Morgan Kaufmann (1994) : Fast algorithms for mining association rules. In: Proc. 20th int. conf. very large data bases,

[3]. Tanbeer, S.K., Jeong, B.S.,Ahmed, C.F.,: ETRI journal 32(5), 676–686 (2010). A novel approach for mining high-utility sequential patterns in sequence databases.

[4]. Jeong, B.S., Choi, H.J.Ahmed, C.F., Tanbeer, S.K.: Information Sciences. 181(21), 4878–4894 (2011) A framework for mining interesting high utility patterns with a strong frequency affinity.

[5]. Jeong, B.-S., Lee, Y.-K Ahmed, C.F., Tanbeer, S.K.,.: IEEE Trans. Knowl. Data Eng. 21(12), 1708–1721 (2009) Efficient Tree Structures for High-utility Pattern Mining in Incremental Databases.

[6]. Karagoz, P, Alkan, O.K.,.: Crom and huspext: IEEE Trans. Knowl. Data Eng. 27(10), 2645–2657 (2015): Improving efficiency of high utility sequential pattern extraction.

[7]. Goyal, V Bansal, R., and Dawar, S.. In: Proc. Intern. Conf. on Big Data Analytics, 84–98. Springer (2015) : An efficient algorithm for mining high-utility itemsets with discount notion.

[8]. Yu,J, B, Rissanen, Barron, A. J.. IEEE Transactions on Information Theory. 44(6), 2743–2760 (1998) : The minimum description length principle in coding and modeling.

[9]. Ben Yahia and Bouasker, S., S. In: Proc. 30th Symp. on Applied Computing, pp. 851-856. ACM (2015) : Key correlation mining by simultaneous monotone and anti-monotone constraints checking.

[10]. Dimitropoulos, X., Brauckhoff, D., Salamatian, K Wagner, A., IEEE/ACM Transactions on Networking, 20(6), 1788– 1799 (2012) : Anomaly extraction in back-bone networks using association rules.

[11]. Chan, R., Yang, Q., Shen, Y. In: Proc. of 3rd IEEE Int'l Conf. on Data Mining, pp. 19–26. IEEE (2003) : Mining High Utility Itemsets.

[12]. Chi, T.T., Fournier-Viger, P. In: Fournier-Viger et al. (eds). High-Utility Pattern Mining: Theory, Algorithms and Applications, to appear. Springer (2018) : A Survey of High Utility Sequential Patten Mining.

[13]. Chu, C., Tseng, V.S. Liang, T. Applied Mathematics and Computation 215(2), 767–778 (2009) : An Efficient Algorithm for Mining High Utility Itemsets with Negative Item Values in large databases.

[14]. Dam, T.-L., Li, K., Fournier-Viger, P., Duong, H. Frontiers of Computer Science, doi: https://doi.org/10.1007/s11704-016-6245-4. Springer (2018) : CLS-Miner: Efficient and Ef-fective Closed High utility Itemset Mining.

[15]. Dam, T.-L., Li, K., Fournier-Viger, P., Duong, H. Knowledge and Information Systems 52(2), 621–655 (2017) : An efficient algorithm for mining top-k on-shelf high utility itemsets.

[16]. Duan, Y., Fu, X., Luo, B., Wang, Z., Shi, J., Du, X.: Detective In: Proc. 2015 IEEE International Conf. on Communications, pp. 5691–5696. IEEE (2015) : Automatically identify and analyze malware processes in forensic scenarios via DLLs.

[17]. Duong, Q.H., Fournier-Viger, P., Ramampiaro, H., Norvag, K. Dam, T.-L.Applied Intelligence 48(7), 1859–1877 (2017): Efficient High Utility Itemset Mining using Buffered Utility-Lists.

[18]. Duong, Q.-H., Liao, B., Fournier-Viger, P., Dam, T.-L. Knowledge-Based Systems 104, 106–122 (2016) : An efficient algorithm for mining the top-k high utility itemsets, using novel threshold raising and pruning strategies.

[19]. Duong, H., Ramampiaro, H., Norvag, K., Fournier-Viger, P., Dam, T.-L. Knowledge-Based Systems 157(1), 34–51 (2018) : High Utility Drift Detection in Quantitative Data Streams.

[20]. Fernando, B., Elisa F., Tinne T. In: Proc. 12th European Conf. on Computer Vision, pp. 214–227. Springer (2012) : Effective use of frequent itemset mining for image classification.

[21]. Fournier-Viger, P., Gomariz, A., Gueniche, T., Soltani, A., Wu, C.W., Tseng, V.S. Journal of Machine Learning Research, 15,3389–3393 (2014) : SPMF: a Java Open-Source Pattern Mining Library,

[22]. Fournier-Viger, P., Lin, J.C.-W., Duong, Q.-H., Dam, T.-L. In: Proc. 29th Intern. Conf. on Industrial, Engineering and Other Applications of Applied Intelligent Systems, pp. 115–127. Springer (2016) : FHM+: Faster High-Utility Item-set Mining using Length Upper-Bound Reduction.

[23]. Fournier-Viger, P., Lin, J.C.-W., Gomariz, A., Soltani, A., Deng, Z., Lam, H.T. In: Proc. 19th European Conf. on Principles of Data Mining and Knowledge Discovery, pp. 36–40. Springer (2016) : The SPMF Open-Source Data Mining Library Version 2.

[24]. Fournier-Viger, P., Lin, C.W., Wu, C.-W., Tseng, V.S., Faghihi, U.: Mining Minimal High-Utility Itemsets. Proc. 27th International Conf. on Database and Expert Systems Applications, pp. 88-101. Springer (2016)

[25]. Fournier-Viger, P., Wu, C.W., Tseng, V.S.: Novel Concise Representations of High Utility Itemsets using Generator Patterns. In: Proc. 10th Intern. Conf. on Advanced Data Mining and Applications, pp. 30–43. Springer (2014)

[26]. Fournier-Viger, P., Zida, S. Lin, C.W., Wu, C.-W., Tseng, V. S.: EFIM-Closed: Fast and Memory Efficient Discovery of Closed High-Utility Itemsets. In: Proc. 12th Intern. Conf. on Machine Learning and Data Mining, pp. 199–213. Springer (2016)

[27]. Gan, W., Lin, J.C.-W., Fournier-Viger, P., Chao, H.C.: More efficient algorithms for mining high-utility itemsets with multiple minimum utility thresholds. In: Proc. 26th International Conf. on Database and Expert Systems Applications, pp. 71–87. Springer (2016)

[28]. Glatz, E., Mavromatidis, S., Ager, B., Dimitropoulos, X.: Visualizing big network traffic data using frequent pattern mining and hypergraphs. Computing 96(1),27–38 (2014)

[29]. Han, J., Pei, J., Kamber, M.: Data mining: concepts and techniques. Elsevier, Amsterdam (2011)

[30]. Hegland, M.: The apriori algorithm–a tutorial. Mathematics and computation in imaging science and information processing. 11, 209–62 (2005)

[31]. Hong, T.P., Lee, C.H., Wang, S.L.: Mining High Average-Utility Itemsets. In: Proc. of IEEE Int'l Conf. on Systems, Man, and Cybernetics, pp. 2526-2530. IEEE (2009)

[32]. Krishnamoorthy, S.: Efficient mining of high utility itemsets with multiple minimum utility thresholds. Engineering Applications of Artificial Intelligence 69, 112–126 (2018)

[33]. Lan, G.-C., Hong, T.-P. Tseng, V.S.: Discovery of high utility itemsets from on-shelf time periods of products. Expert Systems with Applications 38, 5851–5857 (2011)

[34]. Lan, G.-C., Hong, T.-P., Tseng, V.S.: Efficiently mining high average-utility itemsets with an improved upper-bound strategy. International Journal of Information Technology and Decision Making 11(5), 1009–1030 (2012)

[35]. Lin, J.C.-W., Ren, S., Fournier-Viger, P., Hong, T.-P.: EHAUPM: Efficient High Average-Utility Pattern Mining with Tighter Upper-Bounds. IEEE Access 5, 12927–12940. IEEE (2017)

[36]. Lin, Y.C., Wu, C.W., Tseng, V.S.: Mining high utility itemsets in big data. In: Proc. Pacific-Asia Conf. on Knowledge Discovery and Data Mining, pp. 649–661. Springer (2015)

[37]. Liu, J., Wang, K., Fung, B.: Direct discovery of high utility itemsets without candidate generation, In: Proc. 12th IEEE Intern. Conf. Data Mining, pp. 984–989. IEEE (2012)

[38]. Lucchese, C., Orlando, S., Perego, R.: Fast and Memory Efficient Mining of Frequent Closed Itemsets. IEEE Trans. Knowl. Data Eng. 18(1),21–36 (2006)

[39]. Mukherjee, A., Liu, B., Glance, N.: Spotting fake reviewer groups in consumer reviews. In: Proc. 21st international conference on World Wide Web, pp. 191–200. ACM (2012)

[40]. Naulaerts, S., Meysman, P., Bittremieux, W., Vu, T.N., Berghe, W.V., Goethals, B, Laukens, K.: A primer to frequent itemset mining for bioinformatics. Briefings in bioinformatics 16(2), 216–231 (2015)

[41]. Omiecinski, E.R.: Alternative interest measures for mining associations in databases. IEEE Trans. Knowl. Data Eng. 15(1), 57–69 (2003)

[42]. Pei, J., Han, J., Lu, H., Nishio, S., Tang, S., Yang, D.: H-mine: Hyper-structure mining of frequent patterns in large databases. In: Proc. 2001 IEEE Intern. Conf. Data Mining, pp. 441–IEEE (2001)

[43]. Peng, A.X., Koh, Y.S., Riddle, P.: mHUIMiner: A Fast High Utility Itemset Mining Algorithm for Sparse Datasets. In: Pacific-Asia Conf. on Knowledge Discovery and Data Mining, pp. 196–(2017)

[44]. Qu, J.-F., Liu, M., Fournier-Viger, P.: Efficient algorithms for high utility itemset mining without candidate generation . In: Fournier-Viger et al. (eds). High-Utility Pattern Mining: Theory, Algorithms and Applications, to appear. Springer (2018)

[45]. Ryang, H., Yun, U.: Top-k high utility pattern mining with effective threshold raising Strategies. Knowl.-Based Syst. 76, 109–126 (2015)

[46]. Shie, B.-E., Yu, P.S., Tseng, V.S.: Efficient algorithms for mining maximal high utility itemsets from data streams with different models. Expert Syst. Appl. 39(17), 12947–12960 (2012)

[47]. Song, W., Huang, C.: Discovering High Utility Itemsets Based on the Artificial Bee Colony Algorithm. In: Proc. the 22nd Pacific-Asia Conf. Knowledge Discovery and Data Mining, pp. 3–14. Springer (2018)

[48]. Truong, T., Duong, H., Le, B., Fournier-Viger, P.: Efficient Vertical Mining of High Average-Utility Itemsets based on Novel Upper-Bounds . IEEE Trans. Knowl. Data Eng. DOI:10.1109/TKDE.2018.2833478 (2018)

[49]. Tseng, V.S., Shie, B.-E., Wu, C.-W., Yu., P. S.: Efficient algorithms for mining high utility itemsets from transactional databases. IEEE Trans. Knowl. Data Eng. 25(8), 1772–1786 (2013)

[50]. Tseng, V., Wu, C., Fournier-Viger, P., Yu, P.S. IEEE Trans. Knowl. Data Eng. 28(1), 54–67 (2016) : Efficient Algorithms for Mining Top-K High Utility Itemsets.

[51]. Uno, T., Kiyomi, M., Arimura, H.: LCM ver. 2 In: Proc. ICDM'04 Workshop on Frequent Itemset Mining Implementations. CEUR (2004) : Efficient mining algorithms for fre-quent/closed/maximal itemsets.

[52]. Yao, H., Hamilton, H. J. Data and Knowledge Engineering 59(3), 603–626 (2006) : Mining itemset utilities from transaction databases.

[53]. Yao, H., Hamilton, H.J., Geng, L. In: Proc. of ACM SIGKDD Workshop on Utility-Based Data Mining, pp. 28-37. ACM (2006) : A Unified Framework for Utility-based Measures for Mining Itemsets.

[54]. Yin, J., Zheng, Z. and Cao, L.: USpan Proc. of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining, pp. 660–668. ACM (2012) : an efficient algorithm for mining high utility sequential patterns.

[55]. Yun, U., D. Kim. Future Generation Computer Systems 68, 346-360 (2016) : Mining of high average-utility itemsets using novel list structure and pruning strategy.

[56]. Yun, U., Ryang, H. Applied Intelligence 42(2), 323–352 (2015) :Incremental high utility pattern mining with static and dynamic databases.

[57]. Yun, U., Ryang, H., Ryu, K.H. Expert Syst. Appl. 41(8),3861–3878 (2014) : High utility itemset mining with techniques for reducing overestimated utilities and pruning candidates.

[58]. Yu, C.-V., Fournier-Viger, Tseng, V.-S ,P., Gu, J.-Y. in: Proc. 2015 Conf. on Technologies and Applications of Artificial Intelligence, pp. 187–194. IEEE (2015) : Mining Closed+ High Utility Itemsets without Candidate Generation.

[59]. Fournier-Viger, P.,Wu, C.-W., Tseng, V.S, Yu., P.S.,. Proc. 11th IEEE Intern. Conf. on Data Mining, pp. 824– 833. IEEE (2011) : Efficient Mining of a Concise and Lossless Representation of High Utility Itemsets.

[60]. Zaki, J.M. IEEE Trans. Knowl. Data Eng. 12(3), 372–390 (2000) : Scalable Algorithms for Association Mining.

[61]. Zhang, L., , Su, Y, Cheng, F., Fu, G.,Qiu, J.. Applied Soft Computing 62, 974–986 (2018) : A multi-objective evolutionary approach for mining frequent and high utility itemsets.

[62]. Tseng, V.S ,Zida, S., P., Wu, C.W., Lin, J.C.-W., and Fournier-Viger,. In: Proc. 11th Intern. Conf. on Machine Learning and Data Mining, pp. 157–171. Springer (2015) : Efficient Mining of High Utility Sequential Rules.

[63]. Tseng, V.S ,Zida, S., P., Wu, C.W., Lin, J.C.-W., and Fournier-Viger,. In: Proc. 14th Mexican Intern. Conf. Artificial Intelligence, pp. 530–546. Springer (2015) : EFIM: A Highly Efficient Algorithm for High-Utility Itemset Mining.